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Mobile Edge Computing Empowered Energy Consumption Optimization for Multiuser Power IoT Networks

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Abstract

Mobile edge computing (MEC) has emerged as a promising solution to enhance the computational capabilities of resource-constrained Internet of Things (IoT) devices while optimizing the system energy consumption. In this paper, we propose an energy-efficient resource allocation strategy for multiuser power IoT networks by jointly optimizing the offloading ratio, transmit power, and wireless bandwidth allocation. We design an optimization framework that minimizes the total energy consumption of the system while ensuring the latency constraints of computation tasks. To solve this non-convex problem, we employ an alternating optimization approach, where the offloading decision, wireless bandwidth allocation, and transmit power control are iteratively refined using convex optimization techniques and successive convex approximation (SCA). Simulation results are provided to show that the proposed scheme significantly outperforms the competing approaches in terms of energy efficiency. Specifically, for the MEC system with 6 users, the proposed scheme maintains an energy consumption of approximately 0.1 Joules, reducing the energy consumption of the conventional schemes to less that 40 percentages.

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1. Introduction

Mobile edge computing (MEC) has emerged as a key enabler for low-latency and high-efficiency computing in wireless networks by bringing computational resources closer to end users, thereby reducing the reliance on centralized cloud infrastructure [1, 2]. Recent research on MEC system has focused on optimizing resource allocation, task offloading strategies, and network efficiency, particularly in multi-access heterogeneous network environments. With the increasing complexity of modern applications, including augmented reality (AR), autonomous vehicles, and smart Internet of Things (IoT) devices, MEC architectures must dynamically manage computational and communication resources to ensure optimal performance. One significant trend in recent MEC research is the integration of artificial intelligence (AI) and deep reinforcement learning (DRL) techniques to enable intelligent decision-making for task offloading and resource scheduling [3–5]. These AI-driven approaches help MEC networks adapt to time-varying network conditions and user demands, thereby improving overall efficiency. Another major research is the development of cooperative and federated MEC architectures, where multiple edge servers collaborate to provide seamless computing services while ensuring data privacy and security. Additionally, researchers are exploring energy-efficient MEC designs by leveraging techniques such as energy harvesting, dynamic voltage scaling, and workload-aware resource provisioning to minimize power consumption [6–8]. Security and privacy in MEC systems have also gained significant attention, with novel solutions focusing on blockchain-based authentication, secure multi-party computation, and differential privacy techniques to protect user data. Furthermore, the convergence of MEC with emerging technologies

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such as 5G, integrated sensing and communication (ISAC), and UAV-assisted networks has opened new possibilities for enhancing the scalability and reliability of edge computing services. In particular, UAV-assisted MEC is gaining traction as a flexible solution for providing edge computing capabilities in remote and disaster-stricken areas, where traditional infrastructure is unavailable. As the demand for real-time and intelligent edge computing solutions continues to grow, there are some researches on further enhancing system adaptability, improving energy efficiency, and addressing security challenges to enable next-generation MEC applications [9–11].

The performance analysis of MEC networks has been increasingly focused on energy consumption, recognizing it as a critical factor in the sustainability and efficiency of MEC-enabled applications. Given the resource-constrained nature of edge devices and the high computational demands of modern applications, optimizing energy consumption while maintaining low latency and high-quality service remains a major challenge [12, 13]. A significant work has explored energy-efficient task offloading strategies, where computational tasks are dynamically partitioned and offloaded to MEC servers based on energy-aware decision models. Deep reinforcement learning (DRL)-based approaches have been widely adopted to enable intelligent and adaptive offloading, allowing mobile devices to balance local execution and offloading costs dynamically. Additionally, energy harvesting techniques, such as using solar-powered edge nodes and ambient radio frequency (RF) energy, have been proposed to supplement the power supply of edge devices, extending their operational lifespan and reducing dependence on conventional energy sources [6, 14]. Another important research direction involves optimizing resource allocation in multi-user and multi-server MEC scenarios, where joint optimization of computing, communication, and energy resources is crucial [15–17]. Some novel techniques, including Lyapunov optimization, convex optimization, and game theory-based frameworks, have been proposed to efficiently allocate resources while minimizing energy consumption. In addition, energy-aware MEC architectures are increasingly integrating renewable energy sources and battery-aware scheduling mechanisms to further enhance energy sustainability. Researchers have also explored cooperative MEC frameworks, where nearby edge servers and devices collaborate to share computational resources, thereby reducing overall energy expenditure [18, 19]. Moreover, the trade-off between the energy efficiency and service delay has been investigated, aiming to develop strategies that dynamically adjust task execution policies based on energy availability and latency constraints. In the context of 5G and future 6G networks, the integration of MEC with advanced technologies such as intelligent reflecting surfaces (IRS), non-orthogonal multiple access (NOMA), and reconfigurable intelligent surfaces (RIS) has been explored to further optimize energy consumption in wireless edge networks [20–22]. Security and privacy considerations in energy-efficient MEC systems have also gained some attention on lightweight cryptographic protocols and energy-efficient blockchain mechanisms to ensure secure and low-power data transmissions.

In addition, power IoT networks have been extensively studied from the interplay between communication and computing to enhance efficiency, reliability, and intelligence in modern power systems [23, 24]. As the deployment of smart grids, renewable energy management, and distributed energy resources (DERs) expands, power IoT networks should efficiently handle massive data transmissions and real-time computational tasks to ensure stable and secure energy operations [25, 26]. From the communication perspective, the integration of 5G has been explored to enhance spectral efficiency, reduce latency, and support massive connectivity among IoT devices in power systems [27]. The emergence of ultra-reliable low-latency communication (URLLC) has been particularly beneficial for real-time monitoring and control applications in power IoT, where rapid response is crucial for preventing faults and optimizing grid stability. Moreover, the increasing adoption of low-power wide-area network (LPWAN) technologies, such as LoRaWAN and NB-IoT, has provided cost-effective and energy-efficient solutions for connecting smart meters, sensors, and remote power monitoring devices over long distances. Researchers have also investigated AI-driven network management strategies, where machine learning-based techniques are used to optimize spectrum allocation, mitigate interference, and dynamically adjust network parameters based on real-time energy demand and system conditions.

From the computing perspective, the convergence of edge computing and AI has played a transformative role in enabling real-time data analytics, fault detection, and predictive maintenance in power IoT networks. MEC architectures are increasingly being deployed to process power system data closer to the source, thereby reducing latency and alleviating the burden on cloud data centers. Recent work has explored the integration of federated learning (FL) and distributed AI models within edge-based power IoT networks to enable privacy-preserving analytics while reducing communication overhead. In addition, digital twin technology has been widely studied for virtualizing power grid operations, allowing real-time simulation and predictive optimization using AI-driven models. Energy-efficient computation offloading strategies have been proposed to balance computational workloads between

IoT devices, edge servers, and cloud data centers, minimizing energy consumption while maintaining performance. Furthermore, blockchain-based secure computing frameworks have been introduced to enhance data integrity and trustworthiness in distributed power IoT networks, preventing cyber-attacks and unauthorized data manipulations.

Motivated by the above literature review, we propose an energy-efficient resource allocation strategy in this paper for multiuser power IoT networks by jointly optimizing the offloading ratio, transmit power, and wireless bandwidth distribution. An optimization framework is devised to minimize the total system energy consumption while ensuring that computational tasks meet strict latency constraints. To address this complex non-convex problem, we employ an alternating optimization approach, where offloading decisions, bandwidth allocation, and power control are iteratively refined using convex optimization methods and successive convex approximation (SCA). Through extensive simulations, we demonstrate that the proposed scheme significantly outperforms conventional approaches in terms of energy efficiency. Notably, in the MEC network with 6 users, the proposed strategy maintains an energy consumption of approximately 0.1 Joules, reducing the energy consumption of traditional schemes by more than 60.

2. Multiuser MEC Networks for Power IoT Networks

In this paper, we consider a power IoT network with N energy-constrained devices (e.g., smart meters, sensors) and one MEC server co-located with a base station (BS). Each device i generates a computation task $T_i = (D_i, C_i)$, where D_i denotes the input data size (bits), and C_i represents the required CPU cycles to process D_i. The computational tasks are partially offloaded to the MEC server via wireless links. Let $\alpha_i \in [0,1]$ denote the offloading ratio, where $\alpha_i D_i$ is offloaded to the MEC server, and $(1-\alpha_i)D_i$ is processed locally. The wireless channel between device i and the MEC server is modeled as a Rayleigh fading channel. The uplink transmission rate is,

$$R_i = B_i \log_2\left(1 + \frac{P_i|h_i|^2}{N_0 B_i}\right) \quad \text{(bps)}, \tag{1}$$

where B_i is the wireless bandwidth allocated to device i, P_i denotes the transmit power of device i, h_i represents the instantaneous channel parameter between device i and the MEC server, and N_0 denotes the noise power spectral density. From R_i, the transmission latency for offloading $\alpha_i D_i$ is computed as,

$$t_i^{\text{off}} = \frac{\alpha_i D_i}{R_i} \quad \text{(seconds)}. \tag{2}$$

Accordingly, the transmission energy consumed by device i for offloading is,

$$E_i^{\text{off}} = P_i \cdot t_i^{\text{off}} = \frac{P_i \alpha_i D_i}{R_i} \quad \text{(Joules)}. \tag{3}$$

To compute the local computation at device i, we denote the local CPU frequency of device i as f_i^{loc} (cycles/second). The local computation latency for processing $(1-\alpha_i)C_i$ cycles is,

$$t_i^{\text{loc}} = \frac{(1-\alpha_i)C_i}{f_i^{\text{loc}}} \quad \text{(seconds)}. \tag{4}$$

Then, the local computation energy is,

$$E_i^{\text{loc}} = \kappa_i \cdot \left(f_i^{\text{loc}}\right)^3 \cdot t_i^{\text{loc}} = \kappa_i (1-\alpha_i) C_i \left(f_i^{\text{loc}}\right)^2 \quad \text{(Joules)}, \tag{5}$$

where κ_i is the effective switched capacitance coefficient.

As to the edge computation at the MEC server, the MEC server allocates a CPU frequency f_i^{mec} to process $\alpha_i C_i$ cycles for device i. The edge computation time is,

$$t_i^{\text{mec}} = \frac{\alpha_i C_i}{f_i^{\text{mec}}} \quad \text{(seconds)}. \tag{6}$$

The total latency for device i composed of transmission latency, local computation latency, and edge computation latency is given by,

$$T_i = t_i^{\text{off}} + \max\left(t_i^{\text{loc}}, t_i^{\text{mec}}\right) \quad \text{(seconds)}. \tag{7}$$

Since local and edge computations occur in parallel, the overall latency is dominated by the slower process. For real-time power IoT applications (e.g., fault detection), the total latency should satisfy,

$$T_i \le T_i^{\max} \quad \forall i \in \{1, \dots, N\}, \tag{8}$$

where $T_i^{\max}$ is the maximum tolerable delay.

The total energy consumption for device i is the sum of local and offloading energy,

$$E_i^{\text{total}} = E_i^{\text{loc}} + E_i^{\text{off}} \quad \text{(Joules)}. \tag{9}$$

The system-wide energy consumption is,

$$E_{\text{total}} = \sum_{i=1}^{N} \left(\kappa_i (1-\alpha_i) C_i \left(f_i^{\text{loc}}\right)^2 + \frac{P_i \alpha_i D_i}{B_i \log_2\left(1 + \frac{P_i |h_i|^2}{N_0 B_i}\right)} \right). \tag{10}$$

3. Energy Consumption Optimization

The goal is to minimize E_{total} by jointly optimizing offloading ratios $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_N]$, bandwidth allocation $\mathbf{B} = [B_1, \ldots, B_N]$, and transmit power $\mathbf{P} = [P_1, \ldots, P_N]$, subject to the constraints on the latency, wireless bandwidth, transmit power, and offloading ratio,

$$\frac{\alpha_i D_i}{B_i \log_2\left(1 + \frac{P_i|h_i|^2}{N_0 B_i}\right)} + \max\left(\frac{(1-\alpha_i)C_i}{f_i^{\text{loc}}}, \frac{\alpha_i C_i}{f_i^{\text{mec}}}\right) \leq T_i^{\max} \quad \forall i. \tag{11}$$

$$\sum_{i=1}^{N} B_i \leq B_{\max}, \quad B_i \geq B_{\min}, \quad \forall i. \tag{12}$$

$$0 \leq P_i \leq P_{\max}, \quad \forall i. \tag{13}$$

$$0 \leq \alpha_i \leq 1, \quad \forall i, \tag{14}$$

where (12) denotes the wireless bandwidth constraint, (13) stands for the transmit power constraint, and (14) is the constraint on the offloading ratio.

To solve this non-convex optimization problem, we first decouple this problem into convex and non-convex subproblems, solved iteratively using alternating optimization and successive convex approximation (SCA). Specifically, we consider subproblem 1 aiming to optimize offloading ratios $\boldsymbol{\alpha}$ with fixed $\mathbf{B}, \mathbf{P}$. We formulate the convex subproblem as,

$$\min \sum_{i=1}^{N}\left[\kappa_i(1-\alpha_i)C_i(f_i^{\text{loc}})^2 + \frac{P_i\alpha_i D_i}{B_i\log_2(1+\frac{P_i|h_i|^2}{N_0 B_i})}\right], \tag{15}$$

with the constraints of $0 \leq \alpha_i \leq 1$, and $\frac{\alpha_i D_i}{B_i \log_2(1+\frac{P_i|h_i|^2}{N_0 B_i})} + \max\left(\frac{(1-\alpha_i)C_i}{f_i^{\text{loc}}}, \frac{\alpha_i C_i}{f_i^{\text{mec}}}\right) \leq T_i^{\max}$.

Then, we transform the max constraint by introducing slack variables s_i,

$$s_i \geq \frac{(1-\alpha_i)C_i}{f_i^{\text{loc}}}, \quad s_i \geq \frac{\alpha_i C_i}{f_i^{\text{mec}}}, \quad \frac{\alpha_i D_i}{R_i} + s_i \leq T_i^{\max}. \tag{16}$$

This reformulated problem is convex and can be efficiently solved via KKT conditions or CVXPY.

We further solve for α_i^* by deriving closed-form expressions using Lagrangian duality:

$$\alpha_i^* = \left[1 - \frac{\kappa_i C_i (f_i^{\text{loc}})^2}{\lambda_i + \mu_i \frac{D_i}{B_i R_i}}\right]^+, \tag{17}$$

where λ_i, μ_i are Lagrange multipliers for latency and energy trade-offs.

After subproblem 1, we constitute subproblem 2 by optimizing wireless bandwidth $\mathbf{B}$ and transmit power $\mathbf{P}$ with fixed $\boldsymbol{\alpha}$. The minimum rate requirement is given by computing $r_i = \frac{\alpha_i D_i}{T_i^{\max} - s_i}$, where $s_i = \max\left(\frac{(1-\alpha_i)C_i}{f_i^{\text{loc}}}, \frac{\alpha_i C_i}{f_i^{\text{mec}}}\right)$.

We then minimize $\sum_{i=1}^{N} \frac{P_i \alpha_i D_i}{B_i \log_2(1+\frac{P_i|h_i|^2}{N_0 B_i})}$ by substituting $\gamma_i = \frac{P_i}{B_i}$ as,

$$E_i^{\text{off}} = \frac{\gamma_i \alpha_i D_i}{\log_2(1 + \frac{\gamma_i |h_i|^2}{N_0})}. \tag{18}$$

The above E_i^{off} can be approximated using first-order Taylor expansion around $\gamma_i^{(k)}$.

We further perform the bandwidth allocation via water-filling, where the Lagrangian method is used,

$$\mathcal{L} = \sum_{i=1}^{N} E_i^{\text{off}} + \lambda\left(\sum_{i=1}^{N} B_i - B_{\max}\right). \tag{19}$$

Then, B_i is updated as,

$$B_i^{(k+1)} = \frac{\alpha_i D_i}{\log_2\left(1 + \frac{\gamma_i^{(k)}|h_i|^2}{N_0}\right)}\left(\frac{1}{\lambda^{(k)}}\right). \tag{20}$$

After that, λ is iteratively updated to satisfy $\sum B_i = B_{\max}$.

To update the transmit power, we compute the transmit power as $P_i^{(k+1)} = \gamma_i^{(k)} B_i^{(k+1)}$, where $P_i \leq P_{\max}$ is enforced. If this condition is violated, we set $P_i = P_{\max}$ and recompute B_i.

By combining subproblem 1 and 2, we perform the convergence check for the original optimization problem in (11), where we obtain the updated $E_{\text{total}}^{(k+1)}$ and the iterative procedure terminates if $|E_{\text{total}}^{(k+1)} - E_{\text{total}}^{(k)}| < \epsilon$. The alternating optimization framework iteratively refines offloading ratios, bandwidth, and power allocation. Subproblem 1 leverages convex optimization to update α_i, while subproblem 2 employs SCA and water-filling to handle non-convexity in B_i and P_i. This procedure ensures convergence to a locally optimal solution that significantly reduces energy consumption in power IoT networks. The whole procedure of the proposed solution to the optimization problem in (11) is summarized in Algorithm I.

4. Simulation Results

In this part, we perform some simulations to verify the effectiveness of the proposed scheme for the considered MEC empowered energy consumption optimization strategy in the multiuser power IoT networks. Specifically, the effective switched capacitance coefficient κ is set to 1×10^{-28}, which influences the energy

Algorithm 1 Alternating Optimization for Energy Minimization in Power IoT Networks

Input: $N, D_i, C_i, |h_i|^2, N_0, f_i^{\text{loc}}, f_i^{\text{mec}}, T_i^{\max}, B_{\max}, P_{\max}, \epsilon$
Initialize: $\alpha_i^{(0)} = 0.5,\ B_i^{(0)} = B_{\max}/N,\ P_i^{(0)} = P_{\max}/2,$ $k = 0$
while $\left|E_{\text{total}}^{(k)} - E_{\text{total}}^{(k-1)}\right| > \epsilon$ **do**
  Subproblem 1: Optimize $\boldsymbol{\alpha}$ with fixed $\mathbf{B}^{(k)}, \mathbf{P}^{(k)}$
  for each device i **do**
    Compute $R_i^{(k)} = B_i^{(k)} \log_2\left(1 + \frac{P_i^{(k)}|h_i|^2}{N_0 B_i^{(k)}}\right)$
    Solve $\alpha_i^* = \left[1 - \frac{\kappa_i C_i (f_i^{\text{loc}})^2}{\lambda_i + \mu_i \frac{D_i}{B_i^{(k)} R_i^{(k)}}}\right]^+$
    Update $\alpha_i^{(k+1)} \leftarrow \alpha_i^*$ s.t. $T_i \le T_i^{\max}$
  end for
  Subproblem 2: Optimize $\mathbf{B}, \mathbf{P}$ with fixed $\boldsymbol{\alpha}^{(k+1)}$
  for each device i **do**
    Compute $r_i = \frac{\alpha_i^{(k+1)} D_i}{T_i^{\max} - \max\left(\frac{(1-\alpha_i)C_i}{f_i^{\text{loc}}}, \frac{\alpha_i C_i}{f_i^{\text{mec}}}\right)}$
    Update $\gamma_i^{(k)} = \frac{P_i^{(k)}}{B_i^{(k)}}$ and approximate E_i^{off} via SCA
    Allocate $B_i^{(k+1)} = \frac{\alpha_i D_i}{\log_2\left(1 + \frac{\gamma_i^{(k)}|h_i|^2}{N_0}\right)} \cdot \frac{1}{\lambda^{(k)}}$
    Adjust $\lambda^{(k+1)}$ to satisfy $\sum B_i^{(k+1)} = B_{\max}$
    Update $P_i^{(k+1)} = \gamma_i^{(k)} B_i^{(k+1)}$
  end for
  Convergence Check:
  Compute $E_{\text{total}}^{(k+1)} = \sum_{i=1}^{N}\left(E_i^{\text{loc}} + E_i^{\text{off}}\right)$
  if $|E_{\text{total}}^{(k+1)} - E_{\text{total}}^{(k)}| < \epsilon$ **then**
    Break
  end if
  $k \leftarrow k + 1$
end while
Output: Optimal $\boldsymbol{\alpha}^*, \mathbf{B}^*, \mathbf{P}^*$

consumption of computational tasks. The local CPU operates at a frequency of 1 GHz, while the MEC server has a significantly higher processing capability with a CPU frequency of 10 GHz, allowing for more efficient task execution at the edge. The local computing power is configured at 0.2 W, whereas the computing power at the MEC server is slightly higher at 0.3 W, reflecting the enhanced computational resources available at the edge. The transmission power is set to 0.5 W, which determines the energy consumption for offloading tasks from IoT devices to the MEC server. The wireless communication channel follows a Rayleigh fading model, which is commonly used to characterize small-scale fading in wireless networks, with an average channel gain normalized to unity. Furthermore, the noise power spectral density N_0 is set to 1×10^{-15}, which impacts the signal-to-noise ratio and thereby affects the reliability of data transmission. For system performance comparison on the energy consumption, several competing schemes are considered in this work:

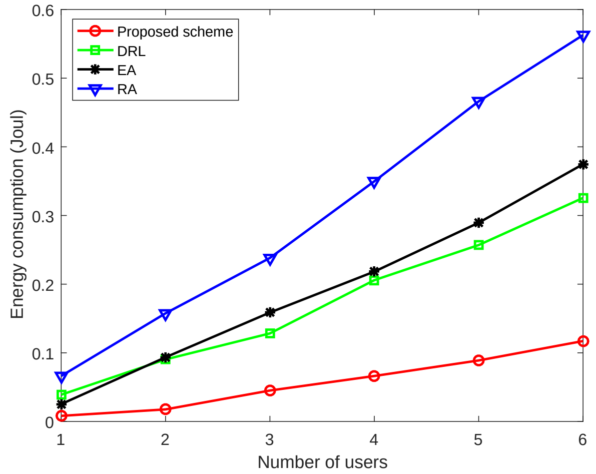

Figure 1. System energy consumption versus the number of users.

- **DRL**: The deep reinforcement learning (DRL) approach leverages reinforcement learning techniques to dynamically optimize resource allocation decisions, including transmit power, offloading ratio, and wireless bandwidth allocation, to minimize system energy consumption.
- **EA**: In equal allocation (EA) scheme, the system resources such as transmit power, offloading ratio, and wireless bandwidth are evenly distributed among users without considering their specific computational requirements or channel conditions.
- **RA**: In random allocation (RA) scheme, the system resources are randomly assigned to users without any optimization strategy, representing a worst-case scenario for energy consumption efficiency.

Fig. 1 illustrates the system energy consumption of the four different schemes versus the number of users, where the total wireless bandwidth is set to 10MHz and the task size of each user is 2MBits. From Fig. 1, one can find that as the number of users increases, all schemes exhibit a rising energy consumption trend, but their growth rates and absolute energy consumption values vary significantly. In particular, the proposed scheme consistently maintains the lowest energy consumption across all user counts, while the RA scheme results in the highest energy consumption. Specifically, when the number of users is 1, the energy consumption of all four

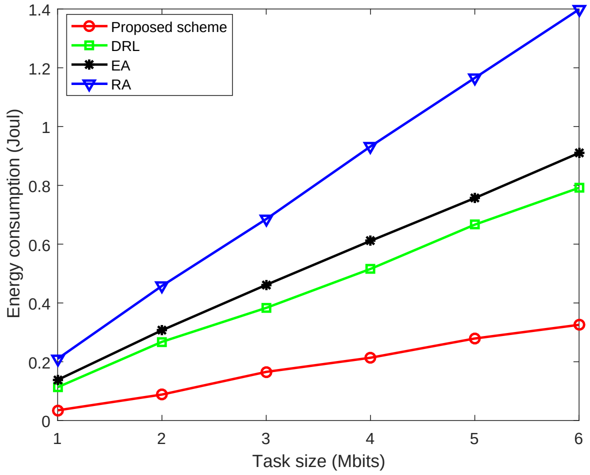

Figure 2. Impact of task size on the system energy consumption.

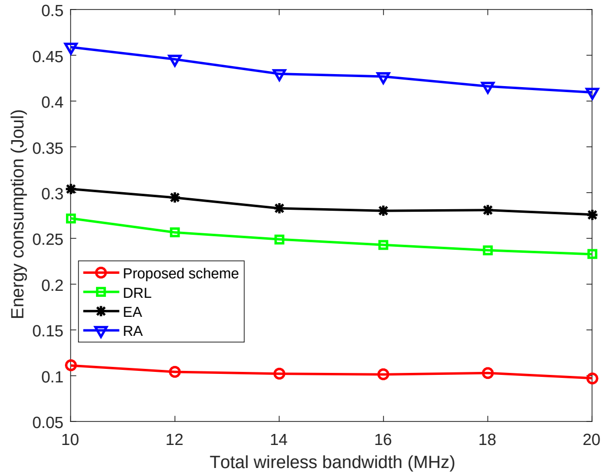

Figure 3. Effect of total bandwidth on the system energy consumption.

schemes is relatively close, but as the number of users increases, the gap becomes more pronounced. When the number of users reaches 6, the energy consumption of the random allocation scheme exceeds 0.5 Joules, while the EA and DRL schemes consume slightly above 0.3 Joules and approximately 0.25 Joules, respectively. In contrast, the proposed scheme remains the most energy-efficient, maintaining an energy consumption of around 0.1 Joules even at the highest user count. This demonstrates that the proposed scheme effectively reduces the system energy consumption, outperforming EA, DRL and EA schemes.

Fig. 2 illustrates the relationship between the system energy consumption and task size while comparing the performance of four different schemes, where there are five users and the total wireless bandwidth is set to 10MHz. One can observe from Fig. 2 that as task size increases, all schemes exhibit a rising trend in the energy consumption, but with noticeable differences in their growth rates. Among the four schemes, the proposed scheme consistently achieves the lowest energy consumption, whereas the RA scheme incurs the highest. At the task size of 1 Mbits, all schemes have relatively low energy consumption, with the proposed scheme consuming nearly 0 Joules, while the RA scheme consumes slightly above 0.2 Joules. As the task size increases to 6 Mbits, the differences among the schemes become more pronounced. The RA scheme experiences the steepest rise, exceeding 1.3 Joules at the largest task size. The EA and DRL schemes also see substantial increases, reaching approximately 0.9 Joules and 0.8 Joules, respectively. In contrast, the proposed scheme maintains a significantly lower energy consumption level, remaining below 0.4 Joules even at the maximum task size. This demonstrates that the proposed scheme is the most energy-efficient, effectively reducing the system energy consumption compared to DRL, EA, and RA schemes.

Fig. 3 illustrates the impact of total wireless bandwidth on the system energy consumption while comparing the performance of four different schemes, where there are five users and the task size of each user is 2MBits. We can observe from Fig. 3 that the system energy consumption is increased with a larger number of users or task sizes, showing a decreasing trend in the energy consumption as wireless bandwidth increases for all schemes, although the rate of reduction varies. Among the four schemes, the proposed scheme consistently achieves the lowest energy consumption across all bandwidth values, while the RA scheme results in the highest energy consumption. At 10 MHz, the proposed scheme exhibits the lowest energy consumption, close to 0.1 Joules, while the DRL and EA schemes consume around 0.27 Joules and 0.3 Joules, respectively. The RA scheme has the highest energy consumption, exceeding 0.45 Joules. As the wireless bandwidth increases to 20 MHz, the energy consumption for all schemes slightly decreases, with the proposed scheme maintaining an energy consumption slightly below 0.1 Joules, the DRL scheme reducing to around 0.25 Joules, the EA scheme stabilizing at approximately 0.29 Joules, and the RA scheme still consuming over 0.4 Joules. Notably, while the proposed scheme achieves the most significant energy efficiency, the RA scheme exhibits the slowest decrease in energy consumption, indicating that it is less responsive to increased bandwidth availability. The comparison results in Fig. 3 highlight the superior energy efficiency of the proposed scheme, as it effectively reduces energy consumption while being more adaptable to varying bandwidth conditions compared to the competing three schemes.

5. Conclusions

This paper proposed an energy-efficient resource allocation strategy for multiuser power IoT networks by jointly optimizing the offloading ratio, transmit power, and wireless bandwidth allocation. An optimization framework was designed to minimize the total system energy consumption while ensuring that computational tasks met latency constraints. To tackle this complex non-convex problem, we adopted an alternating optimization approach, where offloading decisions, bandwidth allocation, and power control were iteratively refined using convex optimization techniques and SCA. Extensive simulations demonstrated that the proposed scheme significantly outperformed existing approaches in terms of energy efficiency. Specifically, in the MEC networks with 6 users, the proposed scheme achieved an energy consumption of approximately 0.1 Joules, compared to 0.25 Joules, 0.3 Joules, and over 0.5 Joules for the DRL, EA, and RA schemes, respectively. Furthermore, as the task size increased to 6 Mbits, the proposed scheme maintained the lowest energy consumption at less than 0.4 Joules, whereas the DRL, EA, and RA schemes consumed approximately 0.8, 0.9, and 1.3 Joules, respectively. These results highlighted the superior energy efficiency of the proposed strategy, making it a promising solution for MEC-enabled power IoT networks.

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